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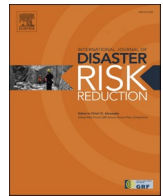
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## Modelling residential habitability and human displacement for tsunami scenarios in Christchurch, New Zealand

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### ABSTRACT

Understanding the potential impacts of a large tsunami on a coastal region enables better planning of disaster management strategies. Potential housing damage, habitability, human displacement and sheltering needs are key concerns for emergency managers following tsunami events. This article presents a novel approach to address these requirements. We first review available literature on factors influencing residential habitability, human displacement and sheltering needs following disasters. Existing models are reviewed to identify lessons, gaps and opportunities that can inform the development of a new model. We then present a new model for estimating habitability, displacement and sheltering needs for tsunami (HDS-T). The model uses an additive scoring system incorporating both physical and demographic factors, weighted according to their relative influence. We demonstrate application of HDS-T through the case study of three tsunami scenarios affecting the coastal city of Christchurch, New Zealand. The results are time-varying, reflecting the response and early recovery phase of the tsunami events. For the largest scenario, 14,695 residents are displaced on the first day, with 1795 displaced residents requiring sheltering assistance. The number of displaced residents reduces to 9014 on Day 4, 7131 on Day 7, and 4366 at the time point of one month. HDS-T is designed to be adaptable to other natural hazards and contexts, such as earthquakes.

### 1. Introduction

Tsunami are powerful natural events that become hazardous if coastal communities are exposed to their effects. The impacts are potentially devastating, as evidenced by the 2004 Indian Ocean and 2011 Great East Japan tsunami events, which resulted in great loss of life and extensive damage to buildings and infrastructure [1–4]. Direct impacts such as casualties and building damage are caused primarily by hydrodynamic and hydrostatic forces, including flow velocity, scouring, inundation, buoyancy effects and impact by entrained debris [5,6]. Indirect impacts to society can be severe and long-lasting, and include human displacement, economic loss, psychosocial impacts, and

disruption to services [5,6]. Inundation extent and amplification effects are influenced primarily by wave height and frequency, local bathymetry and topography [7]. Tsunami impacts depend on the characteristics of the tsunami as well as the vulnerability of exposed assets and populations [6,8]. Understanding the potential impacts of a large tsunami on a coastal region enables better planning and preparedness initiatives to take place [9]. Assessing impacts requires appropriate data on the hazard, the assets and population which are exposed, and modelling techniques suitable for the local context. Issues of housing damage, habitability, displacement and sheltering needs are key concerns for emergency management following natural hazard events including tsunami [10]. Although many risk models provide estimates of building

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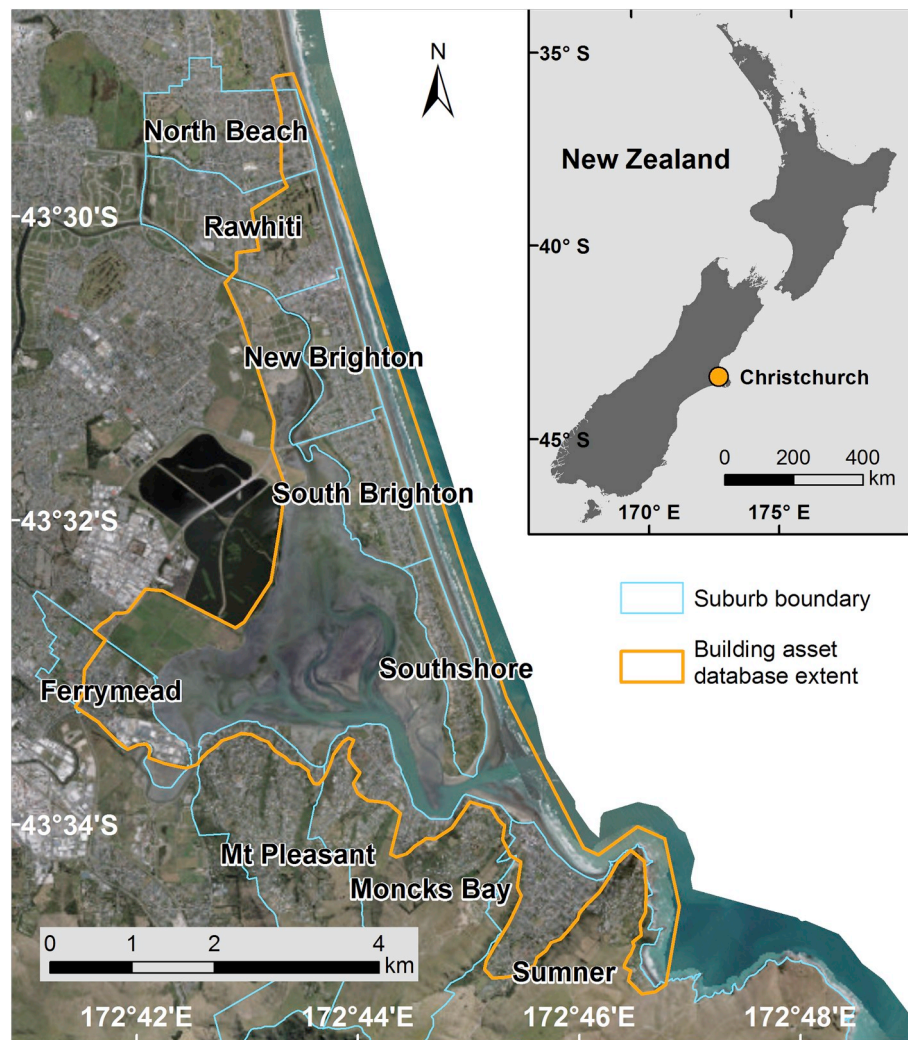
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**Fig. 1.** The study area of coastal Christchurch, New Zealand, showing the main suburbs affected by tsunami inundation modelling. The study area represents the extent of the building asset database (further described in section 4.4.2).

damage or monetary loss, few models provide estimates of habitability, displacement or sheltering needs [11].

The displacement of residents and assessment of sheltering needs during a disaster is a complex process that is influenced by many factors [10,12–15]. These include physical factors (e.g. building damage, loss of utilities), social or demographic factors explaining relative levels of vulnerability, and decision-making by residents exposed to hazards. Four phases of shelter following disasters were identified by Quarantelli [12]: 1) emergency sheltering (evacuation because of an immediate threat, up to one day); 2) temporary sheltering (short-term displacement accommodation, several days); 3) temporary housing (longer-term while repairs are undertaken to residence); and 4) permanent housing (returning to original residence or relocating permanently). These phases continue to show utility throughout many studies, however several stages may be occurring at the same time as recovery processes are complex [10].

Reflecting on the inconsistent definitions of building functionality within the literature [16], we define residential habitability as a dwelling which is safe and healthy to occupy. A dwelling that is uninhabitable will result in displacement of the occupants. Throughout this paper, we also use the term liveability, referring to the relative ability of residents to go about their normal household routines in a dwelling. Liveability is used in recognition that even though a dwelling may be habitable, there may be challenges to living there and assistance may be

required.

This study presents a novel approach to assess habitability, liveability, human displacement and sheltering needs following a tsunami event. We first review the literature on factors influencing residential habitability, displacement and sheltering needs following disasters. Existing models are reviewed to identify lessons, gaps and opportunities that can inform the development of a new model. We then present a new model for estimating habitability, liveability, displacement and sheltering needs for tsunami (HDS-T). The model uses an additive scoring system incorporating both physical and demographic factors, weighted according to their relative influence.

HDS-T is designed to inform potential emergency management demands relating to habitability and displacement following a large tsunami impacting an urban environment, including: how many residents are displaced from their homes, and for how long; of those, how many will require public sheltering assistance; where residents are displaced from; and for habitable dwellings in the affected area, how liveable they are. We demonstrate the application of HDS-T through the case-study of far-field tsunami scenarios impacting the New Zealand coastal city of Christchurch.

### 1.1. Study area

The city of Christchurch is located on the east coast of Canterbury,

New Zealand (Fig. 1). Although tsunami have affected the region several times during the period of European settlement, the impacts have generally been minor due to relatively sparse population, limited asset exposure compared to present levels of coastal development, and fortuitous low-tide during a large tsunami in 1960 [17]. A review of palaeo-tsunami in the Christchurch region also identified 6–7 possible major events occurring in the last 6500 years [18]. Most recently, a tsunami generated by the 14 November 2016 Kaikōura earthquake reached coastal Christchurch. The wave height was small (maximum amplitude of 0.63 m) and no damage was reported within the city, although a large scale evacuation was undertaken [19,20]. Probabilistic modelling of the tsunami hazard to Christchurch suggests the largest contribution to the hazard is from distant sources originating along the subduction zone off South America [6,21]. Tsunami inundation from credible scenarios is limited to coastal suburbs on the eastern and southern edges of the city (Fig. 1).

The low-lying coastal suburbs of Christchurch consist of mainly free-standing residential buildings of one to three storeys. Most are timber-framed construction, with a minority constructed of concrete masonry. Commercial areas consist of a mix of construction types including timber, reinforced concrete, steel and concrete masonry, and are mostly less than three storeys. Within the study area, the usually resident population is approximately 15,400, 54% of homes are owner-occupied and median annual household income is NZ\$62,500 (US\$42,900) [22].

Christchurch suffered major impacts from the 2010–2011 Canterbury earthquake sequence (CES), resulting in significant changes to the coastal suburbs in the study area [23,24]. Many residential dwellings were damaged [25] and required repair or demolition, resulting in the displacement of residents [26,27]. A residential ‘red zone’ was declared encompassing areas at risk to natural hazards across Christchurch City, and the demolition of approximately 7300 properties within the zone has reduced exposure relative to pre-CES [28]. New and repaired buildings are required by Christchurch City Council (CCC) to adhere to stricter building standards regarding materials and height above ground, likely reducing vulnerability to the effects of tsunami inundation. Repair and replacement of infrastructure (e.g. roads, bridges and pipes) are also likely to have improved resilience. However, these improvements to the built environment are counter balanced by subsidence of some coastal areas and uplift of the Avon-Heathcote Estuary which has resulted in a greater risk of inundation and sea level rise [23, 24].

Canterbury Civil Defence and Emergency Management and CCC take a proactive approach to risk management and are engaged with research to understand tsunami hazard and risk across the 4Rs framework (reduction, readiness, response and recovery). CCC use tsunami inundation modelling and risk assessments to inform infrastructure design and town planning. This case study is designed to inform these aspects and allow better planning and preparedness measures to take place.

## 2. Factors influencing residential habitability and human displacement

Modelling residential habitability and human displacement requires an understanding of the factors that influence residents’ decision-making regarding whether to leave or stay. As there are relatively few studies on human displacement and habitability specific to tsunami events or the New Zealand context, we conducted a broad review of relevant literature across all natural hazards and varying international contexts. Relevant literature includes studies on factors influencing human displacement, sheltering following disasters, evacuation decisions, human vulnerability indicators, and functionality or habitability of buildings. The key factors and observations from these studies are summarised here, and an extended literature review is provided in Online Resource 1.

Several literature reviews and case study examinations have been undertaken over recent decades regarding displacement, sheltering,

return decisions and housing recovery following disasters [10,12,13,15, 29,30]. The focus of these studies is primarily on social dimensions of disasters and insights tend to be drawn from case studies of US events such as hurricanes, earthquakes and floods.

Studies on social vulnerability offer further assistance for understanding the demographics of populations that are more or less susceptible to experiencing displacement, and features of the built environment that contribute to vulnerability [31–37]. Research into evacuation decision-making identified many of the same demographic factors that apply to estimating displacement potential [38,39].

Further, studies regarding specific events provide more detail into displacement indicators and return decisions of residents. The most comprehensive studies involving large datasets are for US hurricanes [40–46]. Dickinson [47] examined household relocation in South shore, Christchurch following the CES. Gray et al. [48] explored issues of displacement following the 2004 Indian Ocean tsunami. Detailed studies are especially useful for understanding the relative influence of factors.

Physical factors are shown to have the greatest influence on habitability and displacement [34,36,40–42,45,47,48]. The degree and extent of building damage is the primary factor, followed by utility loss [40–42,44,45,47]. Displacement time is strongly correlated with building damage [40–42,45]. Access, due to damage or exclusion by authorities, must be restored before residents are able to return [6,45]. The amount of damage within neighbourhoods has a significant influence on the ability for residents to get on with their lives, regardless of whether a particular residence is habitable [29,47].

The demographic factors generally observed as important for influencing displacement and return decisions are: income; age (young, and over 65); home ownership versus renting; race and ethnicity; gender; community ties; and education level. Low-income households are more affected by disasters, as they are more likely to rent, inhabit lower-quality housing, and have fewer resources to draw on for recovery [10,12,13,15,46]. Income is particularly important for estimating sheltering needs [30]. Children and the elderly are more vulnerable to the impacts of disasters [15,31], and the elderly tend to be displaced for longer [45]. Residents who own their homes generally have a strong desire to return, whereas renters are less inclined and are often prevented from returning to damaged properties by their landlords [10,12, 34]. Racial and ethnic minorities are more likely to be displaced, explained by minorities generally having lower household incomes and being more likely to rent [35,36,45]. Women are often more vulnerable to disaster effects, however the degree depends on the context, with vulnerability higher in developing countries [31,48]. Residents with strong community ties are more likely to return because of existing social networks, schooling or employment [34,45]. Level of educational attainment is a vulnerability factor that is associated with other factors such as income level and ethnicity [15,31,45].

Weighting of factors in terms of their relative influence is difficult, because they are generally not independent and vary between contexts [15,31,33]. Demographic factors are less important than physical factors for estimating habitability and number of displaced residents [40, 41], but often have a significant influence on displacement time and recovery outcomes. Physical factors are beyond the control of residents, whereas demographics assist in estimating residents’ decision-making and ability to return. Physical and demographic factors are commonly linked, such as lower income neighbourhoods often being in areas that sustain greater damage [13,34]. Studies generally only include the most influential factors in vulnerability or displacement assessments [32,35]. Some factors can have either a positive or negative influence depending on the context [33].

Although there are few studies that deal directly with factors relating to tsunami events or the New Zealand context, most of the indicators are shown to be important across different natural hazards and contexts. The majority of literature are focused on data and learnings from US events, however given the similar level of development between the US and New Zealand, the results should be reasonably transferable. US



**Table 1**

Input factors and outputs of models for estimating displacement and sheltering needs.

Model	HAZUS-MH	ERGO-EQ	MCEER	SYNER-G	Wright et al.	RiskScape	HDS-T
Hazards	EQ, flood, hurricane	EQ	EQ	EQ	EQ	EQ, flood, tsunami	Tsunami
<b>Inputs</b>							
Building damage	✓	✓	✓	✓	✓	✓	✓
Utility loss	✓	✓	✓	✓			✓
Access/Evacuation			✓	✓			✓
Neighbourhood condition			✓				✓
Demographics	✓	✓	✓	✓			✓
Weather		✓	✓	✓			✓
Economic loss (buildings)		✓					
<b>Outputs</b>							
Habitability	✓		✓	✓			✓
No. displaced	✓	✓	✓	✓	✓	✓	✓
Timeframe of disp.					✓	✓	✓
Sheltering needs	✓	✓	✓	✓			✓

Hurricanes are particularly well-studied, and hurricane events have some similarities to distant-source tsunami. Both event types have sufficient warning time to allow evacuation, and direct impacts typically involve inundation, building damage, utility loss and debris, albeit by different physical processes. Therefore, the factors identified across the studies are likely to be relevant for modelling tsunami impacts.

Related to this current study, Scheele et al. [49] developed a survey to gather data on the influencing factors that caused building occupants to move out following recent earthquakes in New Zealand, and the factors influencing their decisions whether to return. 147 responses were received from individuals who had experienced major recent earthquakes in New Zealand, primarily the 2010–2011 CES and the 2016 Kaikōura earthquake. The main reasons for moving out of buildings were building damage, utility outage, and fear of returning (due to aftershocks), in that order. The most important reasons for returning were restoring normal routine, restoration of utilities, being allowed to return and feeling safe to return. There were an insufficient number of responses to examine the influence of factors in detail and the relationships between factors (e.g. return decisions and demographics), however the results reflected the relative influence of factors observed in the literature.

The factors that are useful for modelling habitability and displacement post-disaster are those that can be quantified and for which data is readily available. Most of the factors identified in the literature, are either able to be modelled (e.g. damage) or obtained from publicly available sources (e.g. census data). Finally, given the difficulty of obtaining sufficiently timely and accurate information directly recording post-event residential habitability and displacement [50–52], modelling can help fill this gap for emergency management purposes.

### 3. Existing models

Several published models exist for estimating habitability, number of displaced people and number of people needing shelter post-disaster. Each varies in the natural hazards considered, the input factors and the outputs, summarised in Table 1. The existing models are described here, followed by an identification of gaps and potential improvements for a new model. Vecere et al. [11] reviewed available models, providing additional information that is not otherwise available from primary documentation.

#### 3.1. HAZUS-MH

HAZUS-MH is a plugin for ArcGIS developed by the Federal Emergency Management Agency (FEMA), used to produce loss estimates for natural hazards [53–55]. The models for earthquake, flood and hurricane include modules for estimating displacement and sheltering needs using data at the census tract scale. The earthquake module first estimates residential habitability by calculating the number of

uninhabitable single-family dwellings, defined as having complete damage [55]. The estimate is combined with the number of damaged multi-family dwellings perceived to be uninhabitable by the occupants, defined as moderately damaged or above. The difference is based on the assumption that families in stand-alone houses are likely to wish to remain, whereas those in multi-family dwellings are renters who are unlikely to tolerate damage.

The methodology pairs the uninhabitable dwelling estimates with census data to estimate the number of people displaced, and of those the number seeking public sheltering assistance. The assumptions are that those seeking shelter are low income households, those with young children or aged over 65, are renters, and are more likely to be black or Hispanic. The proportions of the population in each demographic category are multiplied by a weighting factor. The default weighting factors (which sum to 1.0) are 0.73 for income and 0.27 for ethnicity, and zero for both home ownership and age (effectively removing these factors).

The hurricane module in HAZUS-MH follows the same methodology as for earthquakes, except building loss ratios rather than damage states are used to estimate uninhabitable dwellings [54]. The flood module is a modified version of the earthquake module, with sheltering needs calculated based on the number of displaced persons [53]. The inundation area is used to estimate the displaced population, assuming that people will be displaced due to evacuation or lack of physical access to their property because of flooding. Only income and age demographic factors are used to estimate sheltering needs (default weighting of 0.8 and 0.2 respectively).

#### 3.2. ERGO-EQ

ERGO-EQ is a risk software platform for estimating physical, economic and social impacts from earthquakes, developed by the Mid-America Earthquake Center at the University of Illinois [56]. Displacement and sheltering is estimated using one of two methods, either a modified version of HAZUS-MH or logistic regression based on direct economic damage [11]. The first method uses damage states similar to HAZUS-MH, but estimates displacement per building rather than census tract. The same demographic factors (income, ethnicity, home ownership and age) are used to estimate sheltering needs, albeit categorised and weighted differently. The second method uses an algorithm incorporating various social vulnerability factors, and can include modifiers for weather and utility loss [11]. Social factors are associated with damage levels, with the strength of social factors increasing in relation to building damage.

#### 3.3. MCEER

A multi-criteria decision analysis framework was developed by Chang et al. [57] for estimating sheltering needs following an

earthquake. The first decision considers whether a home is uninhabitable, based on building damage and utility loss. If it is habitable, residents' decisions to stay or leave are determined by demographic and liveability factors (e.g. weather, neighbourhood condition). The next decision point is whether residents are physically able to leave, based on distance to shelter, car ownership or age. If residents are forced and able to move, a decision will be made whether to seek public shelter or a more desirable alternative, calculated using income. MCEER forms the basis of several displacement and sheltering needs assessment models.

### 3.4. SYNER-G

SYNER-G is a European research project with the goal of developing fragility models and holistic loss estimations for earthquakes, focused on applicability to European contexts [58]. As part of this project, a model for estimating sheltering needs was developed [59,60], based on the decision framework developed by Chang et al. [57]. The habitability of buildings is estimated by considering building usability (derived from building damage), utility loss and weather. Utility loss is calculated based on context-specific weightings defined by the user, considering the level of service minus the demand, and modified based on weather conditions. Selection of indicators was based on a literature review of commonly cited factors and statistical analysis of European demographic data. Desire to evacuate incorporates household tenure (owning or renting), housing type (single or multi-family), household type (large families with children or single parents), age (elderly and children) and perceived security (recorded crime per 1000 population). Factors for desire to seek public shelter include income, unemployment rate, ethnicity and education level. The outputs are expressed as relative indexes of displacement and sheltering needs, rather than absolute values. The SYNER-G model is the most comprehensive model reviewed here, however has limited applicability to New Zealand without significant modification due to incorporating factors specific to the European context [11].

### 3.5. RiskScape and Wellington earthquake sheltering needs

RiskScape is a joint research programme between GNS Science and the National Institute of Water and Atmospheric Research, which includes the development of a software application (also called RiskScape) for estimating impact and loss from natural hazards [61]. RiskScape version 1.0.3 estimates numbers of displaced people and displacement time based on building damage state, for earthquakes, tsunami and flood modules. The estimate ranges are expressed in months and are targeted towards timeframes of housing repair.

Wright and Johnston [62] adapted the decision framework developed by Chang et al. [57] to estimate numbers of displaced residents following a major earthquake in Wellington, New Zealand. Although many contributing factors were identified, only building damage, water supply loss and building repair times were used to produce the estimates [63]. The RiskScape software was used to calculate building damage states for houses and apartments. Water supply loss and repair times were based on expert opinion. The modelling was an effort to apply the decision framework, and the authors concluded that refinement was needed to include factors such as demographics and neighbourhood liveability.

### 3.6. Application of HAZUS-MH and ERGO-EQ to Christchurch

Vecere et al. [11] identified HAZUS-MH and ERGO-EQ as the most appropriate models for estimating sheltering needs in post-earthquake context, and applied the models to a case study of the 22 February 2011 Christchurch earthquake. The input data used was a ground shaking map of the event from USGS, the RiskScape building database for Christchurch, and census data. Demographic indicators from the models were adapted using the census data as best as possible, and

structural attributes were matched to the closest equivalent in the RiskScape database.

ERGO-EQ outputs resulted in very few residents requiring shelter, explained in part because Christchurch has mostly single-family dwellings, which will only be modelled as uninhabitable if in a 'complete' damage state. The authors suggest further research is needed for the model to produce accurate estimates, as it is expected that partially damaged houses will sometimes result in displacement (and subsequent need for shelter).

Application of HAZUS-MH to the case study resulted in no household displacement or people requiring shelter, again due to no buildings being in a 'complete' damage state. The two default demographic factors in the model were also a poor match for the case study, which had a very low proportion of the most vulnerable groups (Black/Hispanic and household income less than US\$10,000, substituted for Māori based on most common languages spoken and household income less than NZ \$20,000 respectively). Vecere et al. [11] suggest the need for a detailed parametric study of social, physical and economic characteristics of the Christchurch context before either model can be usefully applied.

### 3.7. Gaps and opportunities

The existing models for estimating habitability, displacement and sheltering needs are all useful for their intended purposes and contexts. However, as Vecere et al. [11] demonstrated, existing international models for estimating habitability, displacement and sheltering needs are not easily applied to the New Zealand context. There are currently no published models directly addressing displacement from tsunami events, apart from models of social vulnerability (e.g. Ref. [32]) and a basic estimate in the current version of RiskScape.

The models reviewed here are mostly targeted towards estimating sheltering needs as the primary output. Less emphasis is placed on estimates of building habitability and numbers of displaced residents as useful outputs, and none of the more comprehensive models (with regard to included factors) estimate timeframes of displacement. Models with a time-varying component are currently focused only on longer-term recovery (months to years).

To address these gaps, the new model presented here (HDS-T) is designed to produce estimates of residential habitability and liveability, the number of displaced residents and the timeframe of displacement, and the number of people seeking public shelter. HDS-T is intended to fill the current void for comprehensive displacement modelling in the New Zealand context, by using local data and appropriate fragility functions. In this study, the model is applied to tsunami scenarios, but is designed to be adaptable to other natural hazards such as earthquakes.

## 4. Methodology

### 4.1. Overview of HDS-T model

HDS-T is based on an additive scoring system that assesses the level of habitability and liveability of residential dwellings, and accounts for different levels of social vulnerability and decision-making by residents. Input factors represent physical and social indicators contributing to an overall estimate of habitability, displacement and sheltering needs. Each input factor in the model is given a weighted score that reflects its relative influence. The default weighted scores presented in the following sections are based on the literature review, and are intended to reflect the relative influence of each factor in appropriate proportions. Sensitivity testing of the factor weightings is provided in Section 5. Outputs of the model estimate the number of buildings and people in each habitability category (further described in the next section), the number of people displaced, and the number of people requiring sheltering assistance. The outputs are calculated per meshblock, which is the smallest geographic area for New Zealand census data aggregation, equivalent to census tracts in the US. A flowchart of the HDS-T

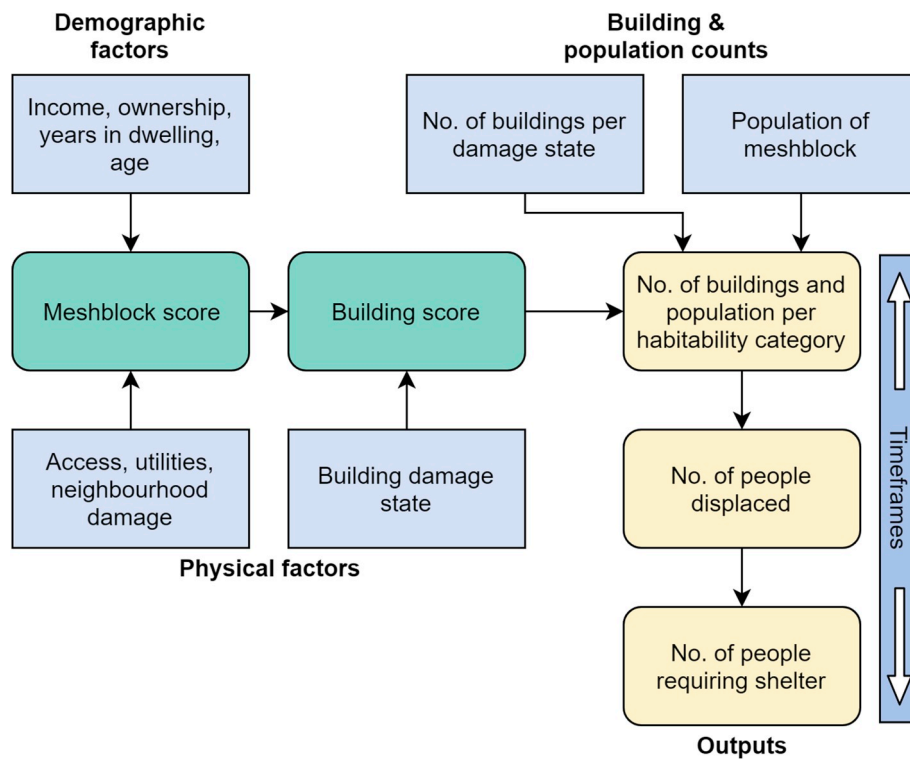


Fig. 2. Flowchart of the HDS-T modelling process.

**Table 2**  
Habitability/liveability categories for residential dwellings.

Habitability/ liveability	Score ( $S_{DWL}$ )	Description
No disruption	0	Fully habitable and liveable
Minor disruption	0.1–0.4	Residents experience minor disruption to household routines
Compromised liveability	0.5–0.9	Difficulty undertaking household routines, residents may require assistance
Uninhabitable	$\geq 1.0$	Residents will be displaced

**Table 3**  
Physical factor scores.

Physical factor	Default score
<b>Access (AC)</b>	
Resident access to property available	0
No access to property for residents	1
<b>Building damage (BD)</b>	
DS0: No damage	0
DS1: Minor damage	0.3
DS2 – DS6: Moderate damage – washed away	1
<b>Electricity (E)</b>	
Electricity available	0
Electricity unavailable	0.2 (summer), 0.4 (winter)
<b>Water (W)</b>	
Water available	0
Water unavailable	0.2
<b>Wastewater (WW)</b>	
Wastewater available	0
Wastewater unavailable	0.2
<b>Neighbourhood damage (ND)</b>	
Less than 5% of buildings in DS2 or above	0
5–20% of buildings in DS2 or above	0.1
>20%–50% of buildings in DS2 or above	0.2
>50% of buildings in DS2 or above	0.3

modelling process is shown in Fig. 2.

The HDS-T modelling process is a framework that can be applied to different hazards and contexts. The following sections describe the scoring system, how factors and weightings are derived, and the equations used for modelling. These sections are described with reference to the Christchurch case study, however are intended to be generic enough to demonstrate how the model could be applied to different case studies. The detailed description of how HDS-T is applied to Christchurch follows in Section 4.4.

#### 4.2. Scoring system of HDS-T

The scoring system is devised to be able to estimate levels of habitability and liveability, rather than a binary option of habitable or uninhabitable. A fully habitable dwelling with no disruption has a score of zero, and an uninhabitable dwelling has score of at least 1.0. Scores between these values represent different levels of liveability. Descriptions and scores for each category are shown in Table 2.

The input factors to the HDS-T model are grouped into either physical or demographic factors. Physical factors are positive scores if they contribute to loss of habitability or liveability. For example, if electricity is unavailable in a meshblock it will receive a score (default 0.2), whereas if electricity is available no score will be added for that factor. Demographic factors may be positive or negative, depending on whether they increase or reduce the likelihood of residents returning to their homes.

All physical factors are related to meshblocks, except building damage which is assessed for individual buildings. Demographic factors are aggregated into a single score per meshblock that acts as a modifier to habitability scores derived from physical factors. This is necessary because demographic information is not available at the scale of individual buildings. The resulting assumption is that physical impacts are independent of household demographics.

The overall method for calculating habitability/liveability categories for dwellings is described here. Further description of each input factor and the scoring system is provided in the following sections. First, a

score is calculated for each meshblock by combining the scores for all physical and demographic factors, except building damage:

$$S_{MB} = S_{PF} + S_{DF} \quad (1)$$

where  $S_{MB}$  is the meshblock score,  $S_{PF}$  is the total score for physical factors within the meshblock, and  $S_{DF}$  is the total score for demographic factors within the meshblock. The constituent factors for  $S_{PF}$  and  $S_{DF}$  are combined using the methods shown in Eqs. (4) and (5) respectively. The meshblock score is then added to the weighted scores for building damage states to calculate a score for each dwelling:

$$S_{DWL} = S_{MB} + S_{BD} = S_{PF} + S_{DF} + S_{BD} \quad (2)$$

where  $S_{DWL}$  is the dwelling score and  $S_{BD}$  is the score related to building damage state for each dwelling. All dwellings in the same damage state within a meshblock are given the same dwelling score. The habitability/liveability category is assigned based on the dwelling score (Table 2), and a count of dwellings in each category is calculated.

Where access is unavailable, or the dwelling damage state is moderate or greater (physical factors with scores of 1, see Table 3), dwellings are automatically categorised as uninhabitable. In these cases, the demographic score is not applied because residents are unable to reoccupy regardless of their circumstances or decision-making.

The population within each meshblock is distributed proportionally across all dwellings, providing the number of residents in each category:

$$R_{HC} = R_{MB} \times D_{HC} \div D_{MB} \quad (3)$$

where  $R_{HC}$  is the number of residents in the habitability category,  $R_{MB}$  is the number of residents in the meshblock,  $D_{HC}$  is the number of dwellings in the habitability category and  $D_{MB}$  is the number of dwellings in the meshblock.

All residents in dwellings regarded as uninhabitable will be displaced. A proportion of those displaced will require sheltering assistance (Section 4.3.3). The outputs vary over time reflecting the response and recovery process, such as restoration of access and utilities. The model may be run to calculate outputs for any point in time (e.g. Day 1, 4, 7 etc.), provided the input data reflects the changing situation.

### 4.3. Factors and weightings

#### 4.3.1. Physical factors

The primary physical factors which affect habitability are access, building damage and utility disruption. These factors are generally beyond the control of residents. To account for community disruption, an additional factor of neighbourhood damage is included. The default scores for each physical factor are shown in Table 3.

All physical factors which are related to meshblocks are combined into a single score ( $S_{PF}$ ):

$$S_{PF} = S_{AC} + S_E + S_W + S_{WW} + S_{ND} \quad (4)$$

where  $S_{AC}$  is the score for access in the meshblock,  $S_E$  is the score for electricity in the meshblock,  $S_W$  is the score for water in the meshblock,  $S_{WW}$  is the score for wastewater in the meshblock and  $S_{ND}$  is the score for neighbourhood damage. The building damage score ( $S_{BD}$ ) is assessed for individual buildings and applied in Eq. (2).

Access refers to the ability of residents to occupy their homes. Access can be impeded due to forced evacuation by authorities, or a variety of physical impediments such as debris, inundation, closed roads, contamination and exclusion zones [6,16]. This factor is binary, with any dwelling that lacks access considered effectively uninhabitable. For the Christchurch case study, access is estimated via expert judgement (see Section 4.4.4).

Building damage is modelled for individual buildings based on appropriate fragility functions which output damage states. The definition of damage states is important for determining the effect on

**Table 4**

Damage state classifications and descriptions for fragility functions from Suppasri et al. [64].

Damage state	Classification	Description	Condition
0	No damage	No damage to building	Possible to use immediately
1	Minor damage	There is no significant structural or non-structural damage, possibly only minor flooding	Possible to be used immediately after minor floor and wall clean-up
2	Moderate damage	Slight damage to non-structural components	Possible to be used after moderate repair
3	Major damage	Heavy damage to some walls but no damage to columns	Possible to be used after major repair
4	Complete damage	Heavy damages to several walls and some columns	Possible to be used after a complete repair and retrofitting
5	Collapsed	Destructive damage to walls (more than half of wall density) and several columns (bent or destroyed)	Loss of functionality (system collapse). Non-repairable or great cost for retrofitting
6	Washed away	Washed away, only foundations remain; totally overturned	Non-repairable, requires total reconstruction

habitability [16]. For this study, the fragility functions and damage state definitions are those developed by Suppasri et al. [64]; described in Table 4. Buildings with only minor damage are able to be reoccupied immediately after minor clean up, experiencing no impacts that would render the dwelling uninhabitable without other negatively contributing factors. Buildings which are moderately damaged require repair to non-structural components, rendering them uninhabitable for a minimum of one month based on repair and displacement times from flooding events in New Zealand and the United Kingdom [65,66]. All buildings experiencing at least moderate damage are considered uninhabitable for the timeframes in this model. If different fragility functions were applied to HDS-T, the effect on habitability would need to consider the defined damage states associated with those functions. Displacement time is strongly correlated with building damage, especially when repairs are necessary before reoccupation [36,45].

Disruption to utilities follows building damage as one of the most important factors influencing the return decisions of residents [40–42]. Each of the primary utilities of electricity, water and wastewater are weighted with a score of 0.2 by default. There is insufficient evidence in the literature regarding the relative importance of each utility. However, electricity is commonly used for cooking and heating in New Zealand, with approximately 93% of households using electricity for heating within the study area, and 79% nationally (2013 Census data; [22]). In winter, the requirement for electricity will be significantly higher for the majority of households [57], and a higher weighting to this factor should be given (default 0.4). Utility outage is estimated via expert judgement for the Christchurch case study (see Section 4.4.4), however the HDS-T modelling framework can accept estimates from more detailed utility outage assessments if available.

Neighbourhood damage is defined by the proportion of buildings within an area (e.g. suburb) that are at least moderately damaged ( $\geq DS2$ ). This factor is included in the model as a proxy indicator for local community disruption. Higher levels of neighbourhood damage are likely to be associated with disruptions such as closed community facilities and shops, damaged roads, and population displacement [29]. Even if a dwelling is habitable, residents may face difficulties if there is disruption in the surrounding community [47].

#### 4.3.2. Demographic factors

Demographic factors can assist in assessing the relative vulnerability



**Table 5**  
Demographic factor scores.

Demographic factor	Code	Default score
<b>Household income (HI)</b>		
< NZ\$30,000 (US\$20,600)	HI1	0.5
NZ\$30,000 – \$70,000 (US\$20,600–\$48,100)	HI2	0.1
> NZ\$70,000 (US\$48,100)	HI3	−0.1
<b>Ownership (O)</b>		
Own home	O1	−0.3
Renting	O2	0.3
<b>Years resident (YR)</b>		
<1 year	YR1	0.3
1–4 years	YR2	0.2
5–9 years	YR3	−0.2
≥10 years	YR4	−0.3
<b>Age (AG)</b>		
15–65 years old	AG1	−0.1
<15 or >65 years old	AG2	0.2

of residents to displacement and sheltering needs, and partially account for decision-making regarding whether to return to a building that is habitable but may have disruptions impacting liveability. The factors included in the model are household income, home ownership or renting, number of years resident, and age (<15 and >65 years). These factors were selected as they are commonly described in the literature as having a significant influence on displacement [15,29,31,33,34,36,45,48], are common to most contexts, and are readily available via census data.

Each demographic factor in the model must have both positive and negative components, to describe whether a resident is more or less likely to be displaced given the physical habitability/liveability score for a dwelling. The default scores for each factor are shown in Table 5.

Demographic factors are combined into a single score per meshblock ( $S_{DF}$ ), based on the proportion of residents in each demographic group:

$$S_{DF} = \sum_{i=1}^3 P_{HIi} \times S_{HIi} + \sum_{i=1}^2 P_{Oi} \times S_{Oi} + \sum_{i=1}^4 P_{YRi} \times S_{YRi} + \sum_{i=1}^2 P_{AGi} \times S_{AGi} \quad (5)$$

where P is the proportion of residents in each demographic group, S is the score for each demographic group, HI refers to household income, O refers to ownership, YR refers to years resident and AG refers to age.

Household income is consistently described as the most important demographic factor influencing likelihood of displacement (e.g. Refs. [10,29,60]). Income bands are based on census data categories. Low income households are strongly weighted towards displacement, as they are less likely to have the resources required to quickly recover and reoccupy [10,13,31,34,45].

Home ownership is a strong indicator of return decisions, with those owning homes having a strong preference to return [10]. Renters are likely to prefer to seek alternative accommodation, and may be prevented from reoccupation by landlords until repairs are complete [12,34]. In New Zealand, either the landlord or tenant can apply for the tenancy to end if the property is destroyed or seriously damaged, and conditions are negotiable for repairable damage. The default scores reflect the strong difference in return decisions.

Reflecting community ties, the number of years resident is included as a proxy indicator. Residents with strong community ties are less likely to want to relocate, due to factors such as social networks, schooling or employment [34,45].

Young people and the elderly have been found to be more vulnerable to disaster impacts [15,31], and older people are more likely to be displaced for long time periods [45]. The proportion of the population under 15 and over 65 years are given a higher vulnerability score.

Demographics are frequently linked [31,45], for example lower household income is more commonly associated with renting. Because of this, it is unlikely that including additional frequently associated

**Table 6**  
Percentage of residents requiring sheltering assistance for each household income band.

Household income (IS)	Code	Percentage requiring shelter
< NZ\$30,000 (US\$20,600)	IS1	30% require shelter
NZ\$30,000 – \$70,000 (US\$20,600–\$48,100)	IS2	15% require shelter
> NZ\$70,000 (US\$48,100)	IS3	2% require shelter

factors will provide a significantly more accurate result given existing uncertainties. For example, educational attainment is associated with household income and age, and ranks lower as a descriptive variable for vulnerability [31,60], therefore inclusion is not deemed necessary. However, where data is available and if the user chooses, further factors may be included.

A strong demographic indicator frequently identified in the literature is race and ethnicity. Although census data is available, this indicator is not included in the model as there are insufficient published studies on the relationship of racial and ethnic vulnerability to natural hazards and displacement in New Zealand. Unlike common factors such as income and ownership, it is not appropriate to apply data on minorities from international studies. This is because the racial, ethnic and cultural makeup in New Zealand is different to international contexts such as the US, where most displacement studies originate. Further, Elliott [36] found racial indicators diminished when controlled for household income, family structure and renting.

Weighting of factors is difficult because the factors are contextual and generally not independent [31,45], and because of a lack of research into the relative influence of factors and the return decisions of residents [10,15]. Esnard et al. [33] describe some of the issues with creating a displacement index using indicator variables, such as the lack of data for some variables identified via literature review and the difficulty of obtaining up-to-date data on variables that change frequently. A lack of literature on the directional effect of individual variables was noted as being highly problematic, particularly as some indicators can be both positive and negative with regards to displacement potential. Because of these issues, users of HDS-T may want to alter the default scores considering the specific local context of application.

#### 4.3.3. Sheltering needs

The strongest indicator for whether displaced residents are likely to seek public shelter is household income [10,30]. The percentage of residents requiring shelter in each household income band is shown in Table 6.

The calculation of sheltering needs for each meshblock is:

$$R_{SH} = \sum_{i=1}^3 P_{ISI} \times R_{ISI} \times R_{UHC} \quad (6)$$

where  $R_{SH}$  is the number of displaced residents requiring shelter in the meshblock, IS refers to the household income band, P is the proportion of residents in each household income band, RS is the percentage of displaced residents requiring shelter in each household income band and  $R_{UHC}$  is the number of residents in the uninhabitable category in the meshblock.

Data on income for those seeking sheltering assistance is generally not recorded in New Zealand due to privacy concerns. For this study, the percentage of displaced residents in each income category requiring sheltering assistance has been assigned based on observations from the literature and testing with the case study data. Using the values in Table 6 with the study area census data results in approximately 10.5% of residents requiring sheltering assistance, which is around the mean value across studies cited by Lee and Chen [30] which showed between 3 and 19% of displaced residents sought public shelter.

As described in the previous section, in the HDS-T model demographic factors are first utilised for estimating the number of

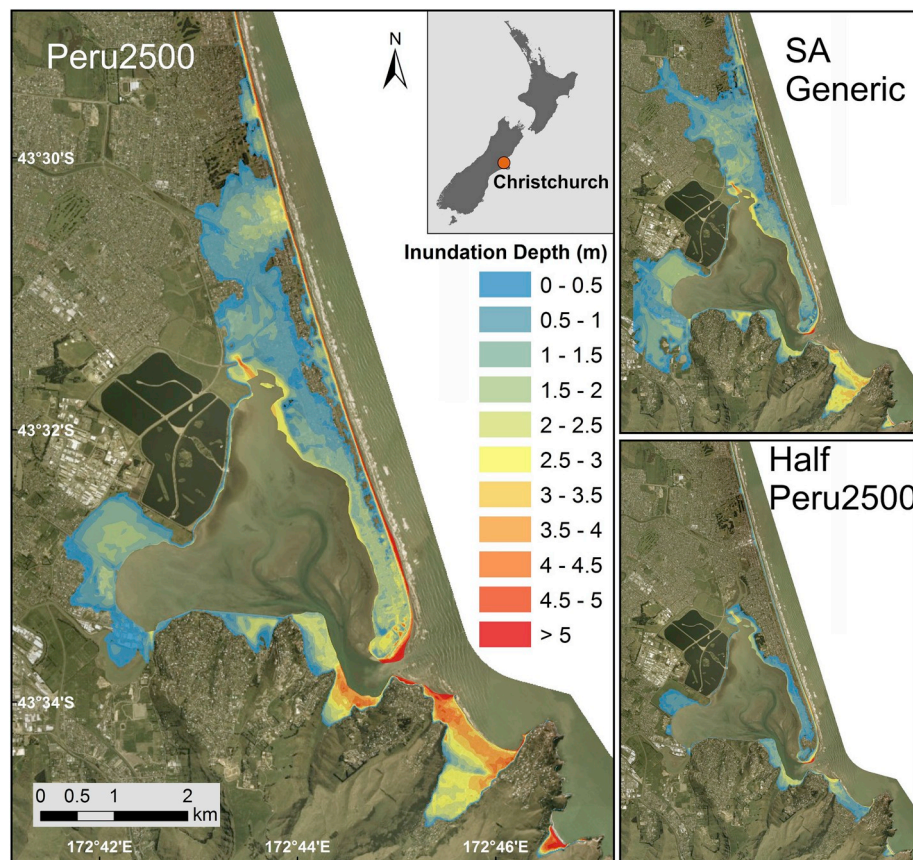


Fig. 3. The modelled inundation depth and extent for each of the three scenarios.

displaced people. This technique is in contrast to most existing models, which assess habitability and displacement based only on physical factors and utilise demographic factors for estimating sheltering needs [11, 54,56,60].

A benefit of using demographic factors to first assess displacement is that the data is associated with the whole meshblock population, rather than assuming the displaced population proportionately reflects the census data. However, it is still necessary to use demographic data to estimate the number of displaced residents requiring sheltering assistance. Household income is therefore utilised a second time in the HDS-T model. The issue of double-counting is minimised as the household income factor is used in different ways, and models using demographic factors for sheltering needs estimates alone will still encounter the same issue of displaced residents not necessarily representing census demographics for a meshblock.

#### 4.4. Application to Christchurch case study

Applying the HDS-T model requires modelling building damage, loss of access and utilities, and obtaining demographic data. For the Christchurch case study, available data sources were sought and created where necessary.

##### 4.4.1. Inundation modelling

Three tsunami inundation scenarios were used for this study, representing distal sources originating from the subduction zone off South America. The inundation depth and extent of the scenarios are shown in Fig. 3. The inundation modelling was performed prior to this study and is documented with publicly available information [67,68].

The Peru2500 scenario is based on an extreme event with a 2500 year return period, as recommended by GNS Science for evacuation planning and emergency management [68]. The tsunami source is a  $M_W$

9.5 earthquake occurring in the subduction zone off the coast of Peru, which has been identified as a major tsunami hazard source for the Canterbury coast [21,68]. The modelling assumed arrival of the largest wave coinciding with Mean High Water Spring (MHWS), and resulted in water levels between 4 and 10 m above MHWS. The maximum flow velocities were between 2 and 3 m/s, except in at the mouth of the Avon Heathcote Estuary where they were over 5 m/s. The arrival time of the first wave is between 14 and 15 h after fault rupture, with the largest wave arriving between 17 and 20 h after fault rupture. Waves continued to cause disturbances for at least 24 h after the first wave arrival. The delay between fault rupture and first wave arrival should allow a sufficient timeframe for evacuation of the inundation zone to take place.

The HalfPeru2500 scenario is modelled from the same source as Peru2500, with the wave height reduced to half as it enters the eastern boundary of the model grid (approximately 175° W). This scenario represents a tsunami with smaller inundation depths and extent, as well as a shorter return period. Assuming linearity in the deep water this tsunami could nominally be caused by an earthquake of the same dimensions and source characteristics but half the slip, with a magnitude of  $M_W$  9.3.

The SAGeneric scenario simulates a generic tsunami from a South American source entering the eastern boundary of the local grid (210° E; [67]). Instead of modelling the tsunami from source, the inundation characteristics of the 1868 Peru tsunami on the New Zealand coastline (based on historical records) were approximately recreated. The 1868 Peru tsunami was generated by a  $M_W$  9.1 earthquake and had the largest effect on the Canterbury coastline since European settlement of New Zealand, with maximum wave heights of approximately 5 m above MHWS within the present case study area, and similar flow velocities to Peru2500 [67].

The hydrodynamic model used for modelling was RiCOM, which captures many of the physical aspects of tsunami inundation and is well-



**Table 7**

Summary of the number of buildings for each source of attribute data within the database.

Data source	No. of buildings
Field survey	1205
CCC Post-EQ data	174
Manually extrapolated	109
Statistically extrapolated	5006
<b>Total</b>	<b>6494</b>

validated against standard analytical test cases and palaeo-tsunami data from New Zealand [68–71]. The topographic data used for Christchurch were LiDAR data collected in 2011 following elevation changes due to the Canterbury Earthquake Sequence (CES). The bathymetric data include an open-ocean grid combined with coastal New Zealand bathymetry data [68]. The open-ocean grid has a resolution of approximately 2 km, reducing to 500 m at the coast [67,68]. The local grid has a resolution of approximately 10–20 m.

The caveats and limitations of the modelling include uncertainties involving the source locations, characteristics of the source fault rupture, and topographic and bathymetric data [67,68]. The grid created to represent the coastline can deform the shape of bays and estuaries. The effect of drag may significantly alter the onshore propagation of tsunamis. The RiCOM modelling incorporates most hydrodynamic aspects of tsunami propagation and inundation, but also includes some simplifying assumptions [67,68,71]. An enhancement of friction for shallow water locations, however the bed roughness does not vary spatially. Wind-driven wave heights are shown to have little effect on tsunami inundation and therefore the water surface is initially flat within the modelling. Uncertainties in the modelling can be quantified by running multiple simulations, however a degree of epistemic uncertainty will always remain [68].

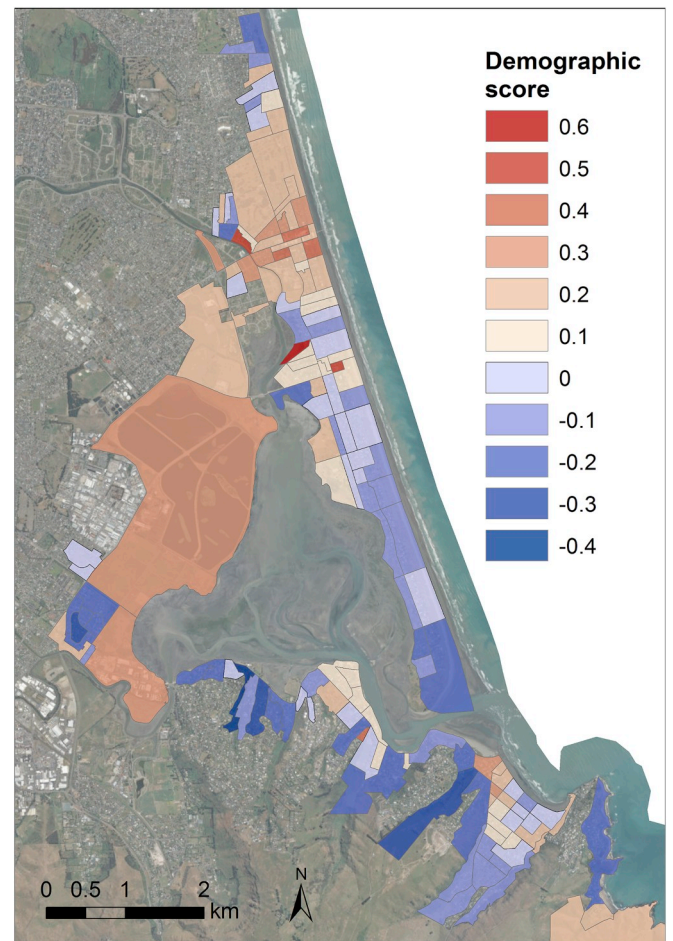
#### 4.4.2. Building and demographic data

An accurate asset database of buildings within the study area is necessary for estimating building damage. The important attributes are the location of buildings; the aspects that are relevant to vulnerability (i. e. construction type, ground floor height, number of storeys); and the building purpose (e.g. residential dwelling, school, commercial).

Although an asset database for the study area was already available as part of the RiskScape software [61], trial surveying within the inundation zone identified that updates were necessary, particularly as the urban zone had changed considerably following the CES. Although the current study is focused only on residential dwellings, buildings of all use categories were surveyed to create a database that is useful for multiple purposes.

Building footprint locations were updated using Google Earth imagery (dated 9 January 2015), by manually removing footprints of demolished buildings and adding new building locations. Post-earthquake structural survey data of some buildings was obtained from CCC, which contained detailed attribute information for many commercial buildings within the study area. Further field surveying of building attributes was undertaken along transects of coastal Christchurch for the purposes of quality assurance. Transects were designed to capture a representative sample of residential buildings, as well as obtain attributes for the majority of commercial and community buildings. The remaining building locations for which attributes were not available had attributes extrapolated statistically (for residential dwellings) or manually (for non-residential buildings) from buildings of similar type which had attributes attached. A summary of the number of buildings and data sources is shown in Table 7.

Demographic data was obtained from the 2013 New Zealand Census meshblock dataset [22]. The aggregated demographic score based on the four demographic factors applied in HDS-T (household income, ownership, years resident, age) is shown per meshblock in Fig. 4.



**Fig. 4.** Demographic score per meshblock of the four combined demographic factors applied in HDS-T.

Positive scores represent an increased susceptibility of the population within a meshblock to being displaced, whereas negative scores are the opposite. The average demographic score across all meshblocks is 0.05. All individual meshblock scores are rounded to 1 d.p. The population per meshblock the count of residents who usually reside within each meshblock from the census data.

#### 4.4.3. Modelling tsunami damage to buildings

The impact of a tsunami on a building depends on two factors: 1) the hazard intensity, in which the flow depth and velocity primarily control the hydrodynamic and hydrostatic forces; and 2) the attributes of the building, such as the type of structure (e.g. light timber vs. reinforced concrete), number of storeys, and ground floor height [72–74]. The direct effects of tsunami on buildings are primarily caused by the following:

- **Inundation:** Direct damage due to water contact, hydrostatic forces on structures
- **Currents:** Hydrodynamic forces acting upon structures
- **Scouring:** Erosion of foundations
- **Buoyancy:** Uplift of structures, especially beneath floor levels, and flotation of materials
- **Debris:** Impact of entrained materials, such as materials from collapsed buildings, vehicles and trees
- **Fire:** Ignition of floating flammable materials

The individual influence of each of these contributing factors is difficult to isolate and may vary significantly between events and

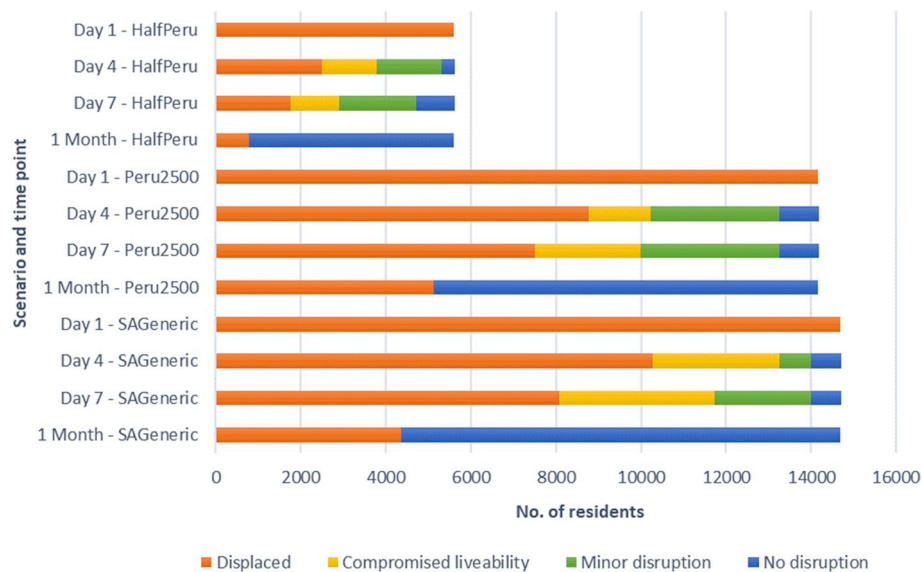


Fig. 5. The number of residents in each habitability category for the three scenarios and time points considered in the case study.

locations [75,76]. Studies using observations and analysis of tsunami damaged buildings have attempted to improve understanding of the relative importance of factors that contribute to damage [72–74]. Yet such post-event studies often find the only factor practical to directly measure is inundation depth, as evidence may be observed in the field whereas the other factors would require data collection as the event unfolds [77]. Although water velocities can be estimated from numerical modelling post-event, they are not necessarily accurate [76]. Debris is also expected to play a strong role in the impact on structures, however there are currently no available models developed for these effects [76,78].

The only reliable hazard intensity measure currently available for assessing tsunami impacts to buildings is therefore inundation depth. Despite the acknowledged limitations it is widely used for tsunami risk assessment for buildings, especially when used at scales larger than an individual building scale. Fragility functions relating inundation depth to the probability of damage, for buildings of different construction types, are the best available vulnerability functions for tsunami impact assessments [76,79].

The fragility functions used in this study are those developed by Suppasri et al. [64]; using empirical data from the 2011 Tōhoku, Japan tsunami. The functions are reasonably transferrable for assessment of structures in New Zealand, particularly due to similar building standards that require construction to withstand frequent seismic activity [79,80]. Due to the lack of empirical data and engineering assessments for tsunami impacts in New Zealand, there are no fragility functions currently available specific to the local context.

There are separate fragility functions for four different construction types: wood (light timber), concrete masonry, steel, and reinforced concrete. For wood and reinforced concrete, separate functions are also available accounting for number of storeys. The damage states from Suppasri et al. [64] are described in Table 4.

#### 4.4.4. Estimating access and utility loss

HDT-S requires access and utility loss as important input factors, preferably with a time varying element to model the response phase and the early stages of recovery. For the present case study, both access and utility loss (for electricity, water and wastewater) were estimated by expert judgement, via informal discussion with Mr Karn Snyder-Bishop (Water and Wastewater Network Operations Engineer at CCC) who has extensive knowledge of the local infrastructure, including interdependencies and impacts following the CES. Modelled building

damage, along with an impact assessment study of tsunami scenarios on Christchurch infrastructure [81] were used as supporting materials, however these assessments are not explicitly linked to the access and utility outage time estimates. This is a simple method of estimating loss of access and utilities, and serves as basic input data for applying the HDS-T model to Christchurch. More detailed estimates could use infrastructure asset data, fragility functions or other more advanced modelling techniques, however these were not available for this study and are beyond the scope of the current work. The HDS-T modelling framework is designed to be able to accept input data derived from a variety of methods, depending on the scope of specific applications.

For the first day of the scenarios, access is assumed to be unavailable throughout the study area as mandatory evacuation orders would be in place. Restoration of access depends on evacuation orders being lifted, debris being cleared, and any remaining health and safety hazards being minimised to an acceptable level. For this case study, it is assumed that the scenarios occur in summer, and the lower electricity factor weighting of 0.2 is used.

Spatial polygons of areas of restricted access and utility outage were created for each time point considered in the modelling (Days 1, 4, 7 and one month onwards). Across the three scenarios, access is generally restored by Day 7. Electricity is restored faster than the other utilities, and is typically available by Day 7 except in highly impacted neighbourhoods (e.g. Sumner). Restoration of water and wastewater will take longer, and only becomes available within the first week in relatively lightly damaged neighbourhoods. It is assumed that all utilities are restored for the time point of one month onwards, reflecting the restoration of the main utility infrastructure to each neighbourhood. Restoration may take longer to significantly damaged buildings, however this will be effectively captured by the damage state (DS2 and above) rendering dwellings uninhabitable.

## 5. Results

The time points considered in the case study (Days 1, 4 and 7) represent the response and early recovery phase following evacuation of the inundation zone for each scenario. The additional time point of one month onwards is included to show the remaining uninhabitable dwellings per meshblock once access and utilities are fully restored, which is of use for assessing the number of residents likely to need temporary housing. These dwellings are those with at least moderate damage (DS2 and above), expected to take at least a month to repair



**Table 8**

Number of residents able to occupy their homes, number displaced but not requiring sheltering assistance, and number displaced requiring sheltering assistance for each time point and scenario.

Time point and scenario	Return/ Remain	Displaced – do not require sheltering assistance	Displaced - Require sheltering assistance
Day 1 - SAGeneric	0 (0%)	12900 (88%)	1795 (12%)
Day 4 - SAGeneric	4424 (30%)	9014 (61%)	1257 (9%)
Day 7 - SAGeneric	6612 (45%)	7131 (49%)	952 (6%)
1 month - SAGeneric	10329 (70%)	4366 (30%)	–
Day 1 - Peru2500	0 (0%)	12428 (88%)	1729 (12%)
Day 4 - Peru2500	5380 (38%)	7745 (55%)	1032 (7%)
Day 7 - Peru2500	6646 (47%)	6621 (47%)	890 (6%)
1 month - Peru2500	9038 (64%)	5119 (36%)	–
Day 1 - HalfPeru	0 (0%)	4992 (88%)	617 (12%)
Day 4 - HalfPeru	3123 (56%)	2225 (39%)	261 (5%)
Day 7 - HalfPeru	3849 (69%)	1575 (28%)	185 (3%)
1 month - HalfPeru	4833 (86%)	776 (14%)	–

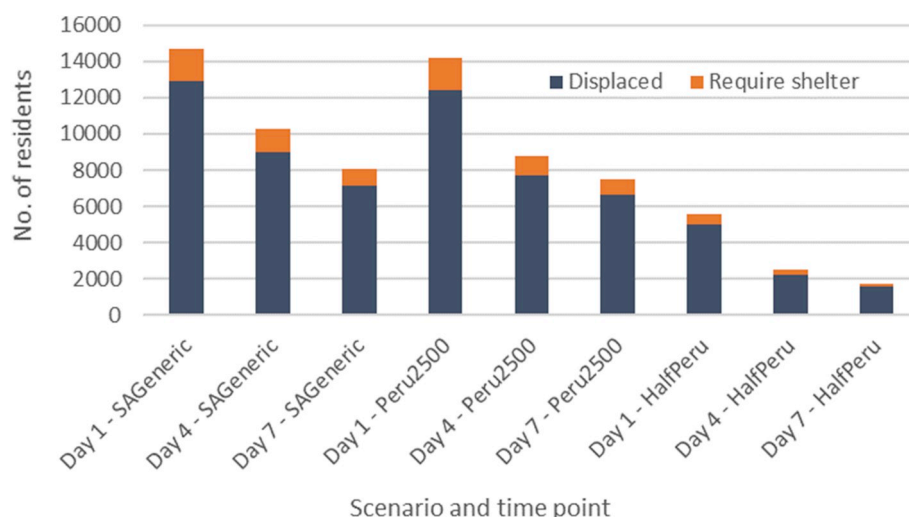
before being habitable. Building damage is the only factor included at this time point.

The habitability category and displacement results for each scenario are charted in Fig. 5 and tabulated in Table 8. A total of 14,695, 14,157 and 5609 people are within the affected inundation area for the SAGeneric, Peru2500 and HalfPeru scenarios respectively. For the first day, all residents are displaced due to evacuation orders. Progressive restoration of utilities and access allows an increase in habitability and liveability across the first 7 days, with a similar relative trend observed across the three scenarios. For the one month time point, SAGeneric and Peru2500 scenarios show 30% and 36% displaced due to housing damage, whereas only 14% are displaced for the HalfPeru scenario. This is primarily related to the extent and depth of inundation, with the first two scenarios being similar, and HalfPeru a much smaller scenario. All results can be displayed showing number of buildings rather than number of residents, if housing is the focus of interest.

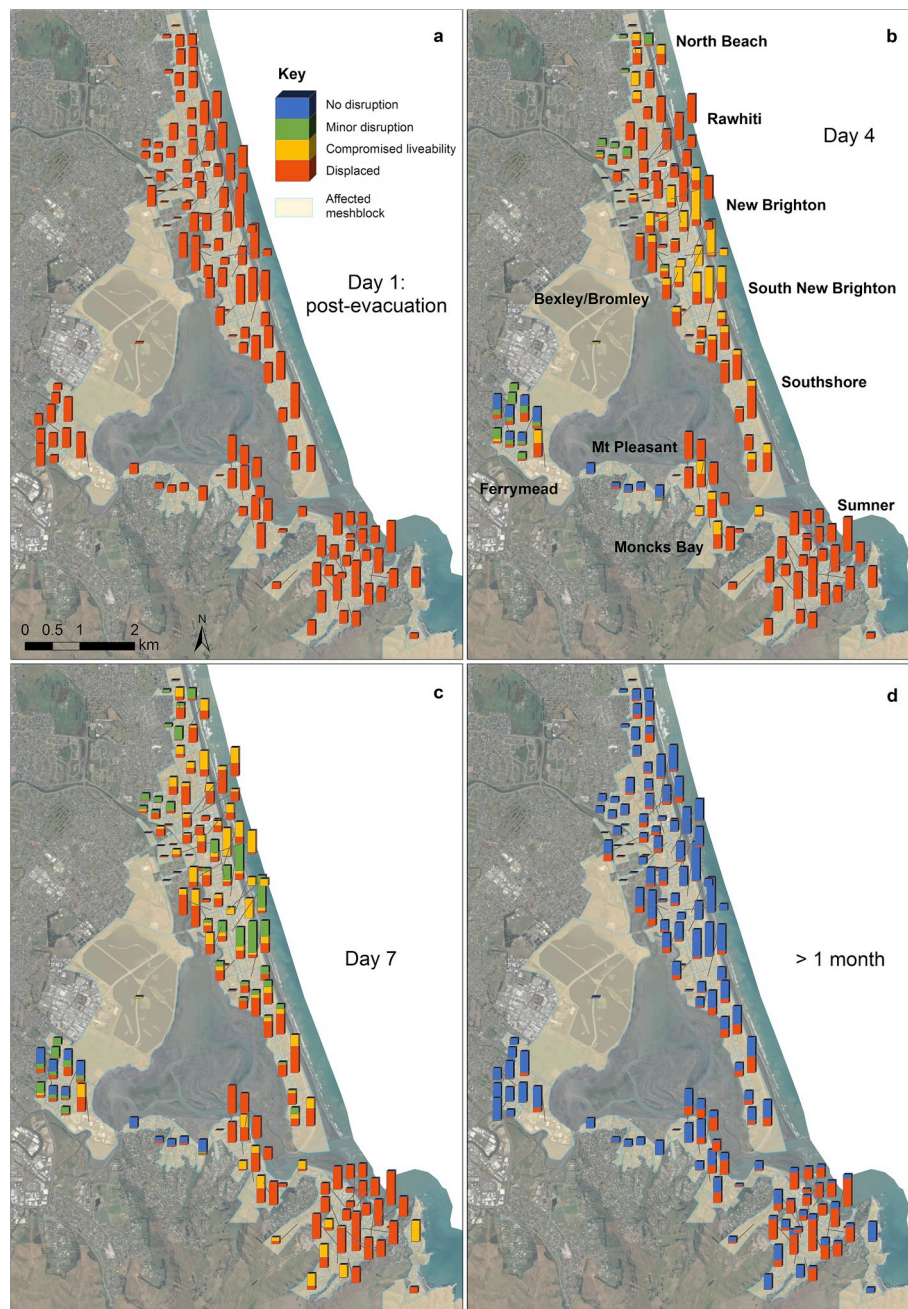
Fig. 6 shows the number of displaced residents and the number requiring sheltering assistance for the first 7 days of each scenario. A similar decreasing trend is observed between the scenarios relative to their magnitude. The number of residents requiring sheltering assistance is a conservative estimate and is based on the assumption that the same proportion of displaced residents will require shelter across the time points. Displaced residents in shelters are likely to attempt to find alternative accommodation as time goes on, especially if it becomes clear that they will not be able to return to their home.

Using the SAGeneric scenario as an example, the habitability and liveability results are displayed spatially per meshblock in Fig. 7. Stacked columns show the relative number of people in each habitability category. Once the results are mapped, a picture emerges of the areas that are more or less impacted, and where response and recovery efforts may be focused. For example, in areas where many dwellings are within the compromised liveability category, temporary services such as water delivery and portable toilets may be needed to maintain habitability.

The results of sensitivity testing to examine the influence of each of the factors on the number of residents in each habitability and liveability category are shown in Fig. 8. Day 7 of the Peru2500 scenario was chosen as a time point and scenario that is likely to be sensitive to the full range of factors included in the model. The influence of each factor is tested by adding or subtracting 0.1 from the default score of each factor (as listed in Tables 3 and 5). Access is excluded from the testing because it is binary (0 or 1). The effect of removing each or all of the demographic factors is also examined. For each tested factor, the percentage change of number of residents in each category is reported. Altering the factor scores may increase or decrease the number of residents in each category (or remain the same). Habitable liveability categories (i.e. residents are not displaced) are generally more sensitive than the “Displaced” category. Neighbourhood damage is the most sensitive physical factor, with category changes between 1.5 and 42.2%. All other physical factors have category changes of less than 5%. Each demographic factor shows a similar sensitivity to changes in scores, between 1.3 and 42.7%. Removing income, ownership or all demographics alters the results in some categories by up to 68.9%. Physical scores are essential to the HDS-T model and therefore sensitivity testing of removal is not conducted, by contrast demographic factors modify the overall scores and may be included or removed. The sensitivity testing results demonstrate the influence of altering the factor scores or removing demographic factors, which can be of assistance for users who may want to alter the defaults.



**Fig. 6.** The number of residents displaced, and of those the number requiring sheltering assistance for each scenario and time point.



**Fig. 7.** Stacked columns showing the number of residents in each habitability category per meshblock and time point for the SAGeneric scenario. Column height proportionately represents population within the meshblocks (the most populated meshblock has 288 people).

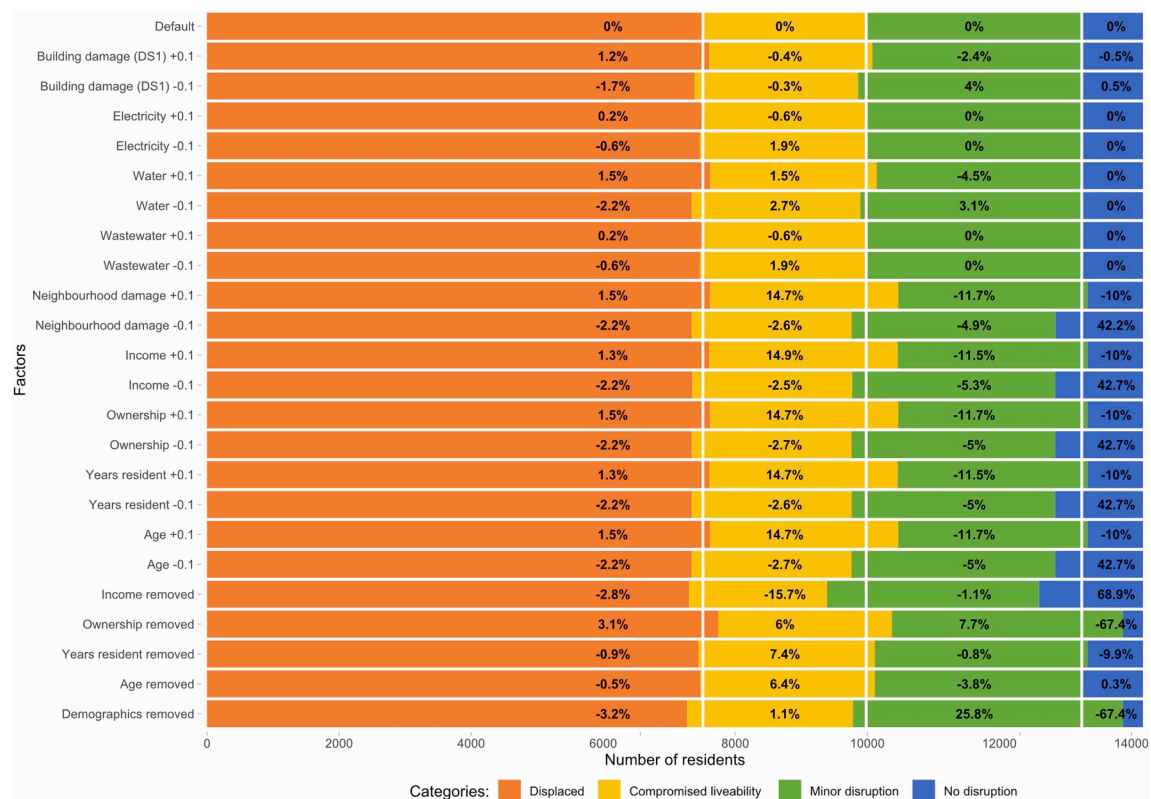
## 6. Discussion

The scoring system of HDS-T has the advantage of allowing a variety of outputs to be produced, depending on the needs of the user. For emergency managers responsible for planning welfare needs, the estimate of the number of residents displaced and those requiring shelter can be of assistance. A unique feature of HDS-T is the ability to quantitatively and spatially describe the various levels of habitability and liveability within the affected area, and the production of time-varying estimates. The habitability results can be of assistance to those responsible for asset management including utility providers, as well as organisations tasked with ensuring the welfare of residents who may wish to return to their homes in various states of liveability.

Results of applying the HDS-T model to the case study of Christchurch produced outputs consistent with expectations. In line with

observations from the literature, the physical factors of building damage and utilities are weighted highly in the scoring system, with demographic factors weighted to have a more moderate effect on estimating whether residents are likely to be displaced, and the perceived habitability or liveability of dwellings. However, HDS-T has not been validated against observations for a real event, because there are no appropriate events for which sufficient data is available for this study.

As with all models incorporating many factors to represent complex situations, a degree of uncertainty exists within each constituent component of the model. First, there is the assumption that the model inputs sufficiently describe the main features of the event. Included in HDS-T are the factors identified in the literature that are commonly cited as contributing to loss of habitability and displacement across different natural hazard events, however these may differ in the case of tsunami and the local context. The scenarios modelled for the Christchurch case



**Fig. 8.** Sensitivity test results of increasing or decreasing the score of each factor by 0.1 relative to the default and removing demographic factors for Day 7 of the Peru2500 scenario. Percentages are the change per category.

study are far-field in origin, allowing for evacuation time of residents. If applied to a local source tsunami scenario, factors such as casualties and widespread destruction (as occurred in the 2011 Great East Japan tsunami) may require modification of the model to account for these effects. Using HDS-T for a real-time situation may be complicated by difficulties in characterising the event (e.g. incomplete hazard information), increasing the uncertainty of the estimates.

Access within the study area was initially estimated by assuming all meshblocks within the inundation zones would be evacuated. Progressive restoration of access was estimated by expert judgement, considering the extent of modelled building damage and knowledge of the local context. Considerable uncertainty exists as there are many contributing factors to access restoration such as road damage, debris and contamination. Due to the complexity of modelling such phenomena, it is likely that future applications of HDS-T will also rely on expert opinion unless more advanced modelling techniques and functions are developed.

Following access, building damage is often cited as the most influential physical factor affecting habitability. Building damage relies on accurate inundation modelling paired with a robust database of buildings with appropriate attributes for applying fragility functions. Care has been taken to use recent inundation modelling and develop a building database as accurate as practically possible. Without empirical or analytical data yet available for developing New Zealand-specific fragility functions, it was necessary to apply functions based on Japanese data, where buildings may respond differently to similar levels of inundation. Further, fragility functions do not explicitly account for all tsunami impacts. Despite the uncertainties, the building damage modelling follows best established practice in line with other modelling of this type.

Second to building damage, the loss of utilities has a strong influence on the habitability and liveability of a dwelling. For this study utility loss was estimated by expert opinion via informal discussion using available

knowledge and resources. As such, a high level of uncertainty exists regarding the impact and timeframes for restoration. Ideally utility loss should be modelled using accurate data on infrastructure paired with fragility functions and estimated repair rates, producing spatial and temporal outputs of utility outage. However, much of the required data was not available for the authors of this study, and appropriate published fragility functions describing infrastructure damage are currently lacking. HDS-T is able to input more advanced utility outage information if it is available, and uncertainty could be managed with outage estimates that provide a range of values.

The demographic factors included in HDS-T are common to many natural hazards and contexts and are also applied in other models of displacement and sheltering needs. As with other studies, census data is used for the study area, which is likely to remain the most accurate and widely available source of demographic data for modelling purposes. Because of the way demographic factors in HDS-T have both positive and negative weightings and are aggregated into a single modifying score per meshblock, additional factors may be easily added. With further research, incorporating factors relating to the experience of minorities regarding displacement and sheltering would be valuable.

Default weightings of both physical and demographic factors are assigned based on examination of their relative influence within the literature and consideration of the local context. Validation of weightings is difficult due to a lack of appropriate data. However, some validation can be achieved by ensuring the scoring system delivers reasonable expected outcomes. For example, physical and demographic factor combinations and their respective weightings (e.g. minor building damage, utilities unavailable, household income > NZ\$70,000, home ownership and so on) can be checked to see whether the summed scores fit within expected categories of habitability. As long as the results of the combinations are appropriate the majority of the time, the model should produce reasonable results. Sensitivity testing of the factor scores can be of assistance for users who may wish to modify the default scores.



Finally, despite uncertainties, the measure of a model of this type is whether it is useful and useable, and can be applied to various scenarios. HDS-T is designed to be able to take input data from a variety of sources, depending on the best available data. Applying HDS-T to other coastal locations in New Zealand that are exposed to tsunami hazard should produce useful results by following a similar method and adopting the default factor weightings. All factor weightings are modifiable by the user. Importantly, the weighting system of HDS-T both allows additional factors but also may be used without them, which is essential for application for scenarios in which data is limited. Demographic factors can be added or removed easily because they are independent of other factors. Adding or removing physical factors would require re-weighting of the physical factors to ensure the scoring system is balanced and produces outputs in line with expectations.

Further development of HDS-T could include greater detail and adjustment for assessing habitability for longer time periods, through into the recovery phase. The model as applied to the present case study only indicates loss of habitability for one month or longer, however more information on repair rates could inform timeframes for restoration of habitability. Although the coastal suburbs of Christchurch mainly consist of free-standing single-family dwellings, many locations have apartment buildings which should be considered differently, such as the greater impact of utility loss. Refinement regarding factors such as the loss of community facilities, the provision of assistance (e.g. water trucks) and effects of contamination could be included with appropriate data.

## 7. Conclusions

HDS-T is a new model aimed at addressing the current gaps in modelling habitability, displacement and sheltering needs for tsunami events and the New Zealand context, and may be used to assist in decision-making for emergency management. The additive scoring system, incorporating weighted physical and demographic factors, allows for a variety of outputs for the purposes of emergency management, housing assessment and infrastructure providers. Quantitative modelling outputs are time-varying and may be visualised spatially, allowing for the creation of diverse communication products depending on the intended purpose. The model can use input data from various sources depending on availability, and factor weightings can be adjusted to suit the local context.

Applying HDS-T to the case study of tsunami scenarios impacting Christchurch produced outputs in line with expectations and knowledge of the local context, and in agreement with observations from international studies on events leading to residential habitability loss and displacement. As with all comprehensive models describing complex events, there are many sources of uncertainty, which can be reduced or quantified depending on the input data used. With appropriate inputs, HDS-T could be modified to be run stochastically and produce a range of estimates, allowing for further sensitivity testing and increased confidence in the results. For example, a range of potential outage times for utilities could be used, and a Monte Carlo simulation employed to assess the impact on the results of changing utility outage times.

Research is ongoing to adapt the HDS-T model to other natural hazards including earthquakes, as well as other contexts. Through this process further refinements will be made that could also improve the model for tsunami impact assessments.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ijdr.2019.101403>.

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